

Performance Evaluation Modeling of Networked Sensors¹

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Abstract—Substantial benefits are promised by operating many spatially separated sensors collectively. Such systems are envisioned to consist of sensor nodes that are connected by a communications network. A simulation tool is being developed to evaluate the performance of networked sensor systems, incorporating such metrics as target detection probabilities, false alarms rates, and classification confusion probabilities. The tool will be used to determine configuration impacts associated with such aspects as spatial laydown, and mixture of different types of sensors (acoustic, seismic, imaging, magnetic, RF, etc.), and fusion architecture. The QualNet discrete-event simulation environment serves as the underlying basis for model development and execution. This platform is recognized for its capabilities in efficiently simulating networking among mobile entities that communicate via wireless media. We are extending QualNet’s communications modeling constructs to capture the sensing aspects of multi-target sensing (analogous to multiple access communications), uni-modal multi-sensing (broadcast), and multi-modal sensing (multiple channels and correlated transmissions). Methods are also being developed for modeling the sensor signal sources (transmitters), signal propagation through the media, and sensors (receivers) that are consistent with the discrete-event paradigm needed for performance determination of sensor network systems. This work is supported under the Microsensors Technical Area of the Army Research Laboratory (ARL) Advanced Sensors Collaborative Technology Alliance.

TABLE OF CONTENTS

1. INTRODUCTION	1
2. SYSTEM CONTEXT AND METRICS	2
3. MODELING APPROACH	2
4. CHOICE OF QUALNET ENVIRONMENT	5
5. EXAMPLE EVALUATIONS	6
6. CONCLUSIONS	9
REFERENCES	9

1. INTRODUCTION

An important emerging technology is networked sensors. In such a system, many sensor “nodes” are spatially distributed throughout an area of interest. Each node contains one or more sensors, a processor, a radio, and an energy supply. The nodes form a network and operate collectively to achieve greater functionality than the sum of their individual parts. However, it is inherently difficult to evaluate the performance of the complex adaptive system formed by the sensor collective using analysis. In this paper, we present a novel approach for deriving the sensing performance of a distributed sensor system using a simulation environment.

The key problem is to quantify the synergy derived from fusion of information collected from many spatially dispersed sensors. While fusion of collocated multi-modal sensors has been extensively studied, the benefits of combining spatially distributed sensors, even of the same modality, have only been pursued relatively recently. Advancements in miniaturized devices (e.g., MEMS sensors) have enabled consideration of deploying arrays of sensor nodes and consequent interest in their performance evaluation. A number of potential applications of sensor networks have been described (e.g., [1], [2]).

Considerable progress has been made in developing sensor network technology through such sources as the DARPA Sensor Information Technology [3] and Power Aware Computing/Communication [4] research programs. Currently, we are participating in the Advanced Sensors Collaborative Technology Alliance (ASCTA), which consists of a powerful consortium of the Army Research Laboratory and a number of academic and industry organizations. Within the ASCTA is the Microsensors Technical Area. While there are varied applications of distributed sensor networks, including Space Science (see [2]), the focus of this paper is our ASCTA Microsensors progress, having Army applications.

While sensor systems have been used extensively for a long

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time, the notion of operating dispersed sensors as a cohesive and autonomous network is fairly recent. A number of advancements have been achieved in developing sensor nodes and in the communications among them. For example, novel information distribution methods, energy-efficient routing and scheduling of activities have resulted in substantial gains in the transmission of bits per meter per joule. Analytical methods (e.g., [5]) have been applied to for distributed sensing. Simulation frameworks have been proposed for integrated evaluation of communications, sensing, and energy consumption [6,7]. Tools exist for sensor placement and mix analyses [8-10] and distributed tracking [11,12], as well as detailed (seismic) sensor propagation [13]; however, these focus on sensing without specific concern for communications aspects. The simulation tool under development in the ASCTA is designed to capture the systems performance stemming from networking in the sense of both sensor fusion as well as communications, and for characterizing operational lifetimes determined by depletion of finite energy supplies.

In the next section, we provide the context for the system for which performance is being derived, including the key entities of interest, and define the metrics. In Section 3, we present the modeling approach used in developing the sensor network evaluation tool. The reasons for our choice of the underlying simulation environment, QualNet, are given next. Performance is derived for illustrative examples in Section 4, followed by conclusions of the work.

2. SYSTEM CONTEXT AND METRICS

The context for our work is a military environment in which there are numerous entities that are dispersed across a geographic region. There are mobile entities that may be vehicles or personnel, or other objects that could confuse sensing. These entities are of different types, such as wheeled vehicles vs. tracked vehicles, or combatant (enemy or friendly) or noncombatant. They are also characterized by their location, and their track (historical and predicted). For simplicity, we will refer to any such entity as a “vehicle” or “target”. The purpose of the sensor system is to provide the “situational awareness” of the targets and their attributes.

Sensors may be deployed in the area of interest. Each target generally emits signals (unintentionally) that may be received by sufficiently proximate sensors. The propagation of the sensor signal will depend on the terrain and environmental factors (e.g., day/night, wind, ground conditions, fog). Sensors having different modalities are beneficial in mitigating different environmental constraints, and can also provide complementary information (“features”) that aid in resolving the target type. Typical sensors are acoustic, seismic, imagers (visual and IR), radar, magnetic and electric field.

The geographic area will typically contain characteristic locations of particular interest or require control. The

problem domain is characterized by the dimensionality of coverage. For example, concern for a choke point may exist, which might be monitored for activity simply by a single sensor node at that location. Greater dimensionality arises in the case of a border, with concern for targets crossing it. This case might be covered using many sensors spread across the linear extent. A closed perimeter is similar, where the line is closed on itself to encircle an area. Another case can arise from constraints in the terrain, such as restricting the vehicle to follow a road. More generally, a two-dimensional region may need to be monitored, as can occur in an unconstrained battlefield context. Furthermore, three-dimensional coverage and characterization may arise in urban environments involving multi-story buildings or underground facilities (e.g., sewer systems) or in complex air-land battle contexts.

It is possible that a long-range stand-off sensor can provide coverage of a large geographic area. However, such assets tend to be limited by resolution, shadowing effects, single point failure risk, vulnerability (such as exposed aircraft), cost and availability (such as satellite-based sensing). Often, the only way to sense particular targets (e.g., armed personnel) is by “in situ” sensors. The microsensor network concept concerns the deployment of many sensors that are relatively close to the targets they are trying to sense. Generally, these are low-cost, small assets and can therefore be “organic” to lower echelon organizational units and deployed rapidly in immediate areas of operation.

The primary sensing performance metrics for microsensor networks are probability of target detection, false alarm rate, precision in locating the position of the target, quality of the target track (spatial and temporal), and target type classification/identification resolution and accuracy. Generally, a variety of sensor modalities are deployed, and of key interest is the optimal “mix” of sensor types for expected scenarios. Primary communications metrics are throughput and latency. Energy consumption is a key metric associated with both sensor processing and communications. For example, processing associated with sensor beamformers consumes considerable power, and therefore these are best utilized when awakened by separate “tripwire” sensors that are able to operate with much less power but unable to provide adequate sensor performance alone.

3. MODELING APPROACH

Our sensor system model is based on the classic (one-way) communications model of Claude Shannon shown in Figure 1:

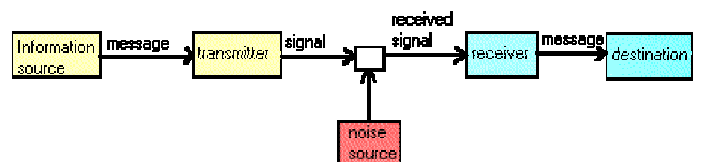


Figure 1 - Shannon's Model of Communication

Recognizing the parallel between a communication system and a sensor system, Shannon's model may be generalized for sensing as shown in Figure 2:

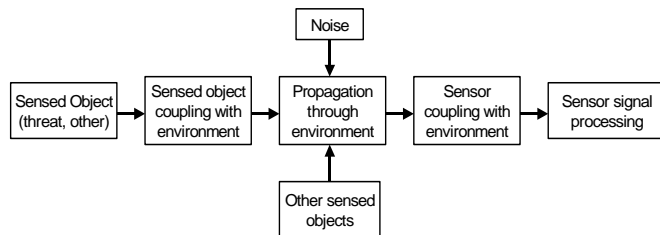


Figure 2 - Model of Sensor System

The key generalization is to replace “communications channel” by the sensor signal medium, shown as “propagation through the “environment” for that sensor modality in Figure 2. For example, a seismic signal will propagate through the ground medium.

The five basic sensor system elements in Figure 2 are described further as follows:

1. Sensed Object. This component identifies the sensed object by name and incorporates all the inherent attributes associated with it. The objective of the sensor system output is to detect and identify this entity as accurately as possible. Several sensor systems may perceive different characteristics of the same object. In an accurate model, the sensed object possesses the union of all the attributes that the sensor systems may determine. Included in this set of attributes are the position characteristics, which include location, velocity, orientation, and track. The near-term focus of the ASCTA sensor network research is concentrated on sensing military vehicles and personnel (and objects that might be confused as such, e.g., animals). These are spatial point sources having continuous presence, differing fundamentally from an object having spatial extent such as a biochemical gas cloud, or an instantaneous event such as an explosion. Abstract attributes such as “having hostile intent” are currently outside the scope of this work. In our current simulation model architecture, it is assumed that the sensor system operations will not affect the behavior of the sensed objects. The sensed object’s motion follows a fixed script. Thus, for example, we currently do not consider the case where an object learns that it has been detected, causing the target to alter its direction of travel.

2. Sensed Object Coupling with the Environment. The sensed object directly “modulates” its “signal” in some fashion, and the extent to which this occurs will depend on the characteristics of how it is coupled with its immediate environment. For example, a tracked vehicle can induce a periodic seismic signal due to “tread slap” (a function of speed and tread spacing). Also, the magnitude of seismic generation will depend on the immediate environmental conditions, such as whether the terrain is rough (potholes)

or damp. As another example, acoustic signal generation by an exhaust pipe will have a preferential direction depending on the current orientation of the vehicle.

3. Propagation through the Environment. For each signal modality, a “channel” is modeled that captures the propagation of the signal through the environment. Essential aspects to model are: (1) the rate of signal attenuation with distance, (2) propagation speed, and (3) directional pattern (if not isotropic). These generally depend on the environment itself, e.g., seismic propagation differs for bedrock vs. sandy terrain; imaging systems will depend on atmospheric conditions (e.g., fog); and acoustic signal propagation will depend on day/night and wind. The simplest model for signal strength propagation is a “cookie cutter” model in which the object is sensed if and only if the sensor is within a given fixed range of the target. Such a model may be defined with different ranges depending on the different targets and attributes being sensed by the same sensor. More sophisticated and accurate propagation models account for gradual signal attenuation, as well as intervening objects between the target and sensor that obscure the signal, such as blockage of a visual imager.

4. Sensor Coupling with the Environment. The sensor itself will be associated with the environment by its position and orientation (if not omni-directional) as well as its immediate interface. For example, a seismic sensor will operate better if it is staked into the ground vs. laid on the surface. In addition, any power consumption requirements of the sensor itself will be quantified.

5. Sensor Signal Processing. The raw sensor signal will be processed and result in actions. This may be detection of a simple threshold excursion that generates a communications act. The output may also generate a command that influences the sensor’s coupling with the environment, such as mechanically slewing a gimbal to a new orientation to center the received signal within the field of view. The output of the signal processing will be associated with the different attributes of the sensed object that are detected and identified (including position/orientation and track aspects), and will stochastically depend on the quality of the signal (as determined by the preceding model components). Bandwidth and quantization/resolution levels of raw and processed signals need to be identified so that communications requirements for subsequent relay can be deduced. Such a representation may consist of a value (e.g., bearing rate) together with an estimate of its uncertainty. In addition to characterization of the possible actions made by received signals, the processing model will also identify the latencies and energy consumed by the signal processing (algorithm complexity and assumed computational engine). Also, any mandatory commands that must be provided prior to processing should be

identified, as well as default values used for initial sensor signal acquisition.

Extensions for modeling multiple targets. Simultaneous sensing of more than one target by a sensor is analogous to the communications case of a multiple access channel, where there are multiple transmitters and a single receiver. Often, random access communications models treat such multiple reception as a “collision” in which the multiple transmitted messages cause destructive interference, and are therefore unusable as messages. Various forms of random access reception have been modeled, including the binary cases of “something – nothing”, “collision – non-collision”, and “success – failure” as well as the ternary case of “idle–success–collision” and generalizations that permit successful reception to some level of multiplicity (such as might occur in a code division multiple access system). “Capture” phenomena may also be modeled. These communications models may be applicable for modeling multi-target sensing, however, it is likely that more accurate models will need to be developed. Linear addition of sensor signals that are then processed algorithmically to derive multi-target information may be expected to be more representative of signal waveforms other than interfering radio signals. Non-linear combining of signals within the environment (“inter-modulation” effects) will require more sophisticated models.

Extensions for modeling multiple sensors. Since our goal is to derive performance of sensor *networks*, it is critical to model targets that are sensed simultaneously by multiple sensors. Two cases may be distinguished: (1) all of the sensors are of the same type (modality), but are spatially separated, and (2) the sensors have different sensing modalities, and may or may not be spatially separated. The case where they have the same modality is analogous to a broadcast communications channel, with one transmitter and multiple receivers. Modeling is straightforward, with signal propagation being dependent on the spatial relationship between the target emitter and each individual sensor.

The case of multiple sensors of differing modalities sensing the same target is depicted in Figure 3. This situation is analogous to having multiple communications channels, one for each sensing modality. However, the signals being transmitted on the different “channels” are correlated, such as the information transmitted about the target location. Other correlations enable association with the same target, such as acoustic and seismic signal spikes both occurring when a vehicle hits a pothole. We therefore show a single source in Figure 3. At the same time, different attributes of the target may be apparent only to a given sensor modality, such as color or metallic content. Therefore, a generalized source transmitter is needed to model these aspects.

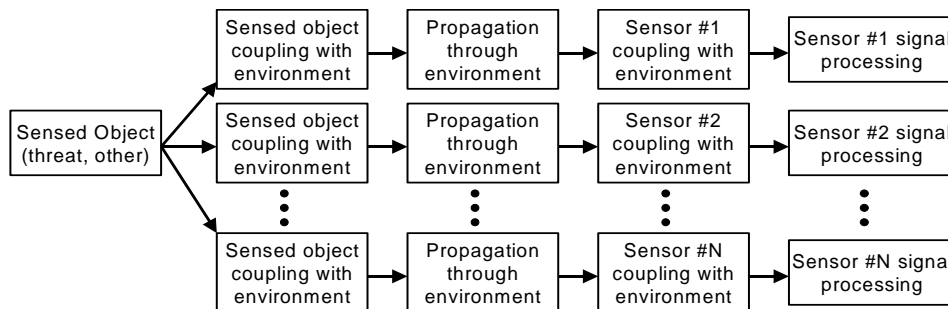


Figure 3 - Multiple sensors detecting a single object

Fusion of information from multiple sensors, whether of the same modality or not, is critical to capturing the synergy of the sensor collective. The distributed signal processing architecture will incorporate decisions regarding the amount of information propagated in the next step in the processing chain (e.g., a simple alert message for sensor cueing vs. forwarding the raw sensor stream for additional processing), as well as how combining of signals and decisions are made. Generally, a node may have multiple sensors, a radio and processing capability, and inputs to the node will come in the form of sensor signals as well as received radio messages. Performance will depend on communications resource consumption, latency, and need for covertness, as well as computational and energy resource demand.

The multiple sensors can combine their results at different levels: direct combining of raw signals (possibly time-

shifted and/or filtered), fusing of different intermediate features extracted by different systems (e.g., energy detected in specific spectral bands), or fusing of attributes decided by different systems (e.g., range and bearing). Modeling of these different methods of sensor system combination will be made explicit in future progressions of this effort. These models will necessarily include communications constraints that add latency and possibly errors in their operations.

It is also noted that sensor system management will dictate when/whether a particular sensor is active. For example, if a sensor is cycled on/off to conserve energy, then the latency before becoming active as well as any initialization delays (e.g., warm up/self calibration, initial signal acquisition) will need to be characterized. Similarly, performance will be affected when a particular sensor system is activated by means of being cued by another sensor system.

4. CHOICE OF QUALNET ENVIRONMENT

As indicated earlier, our goal is to quantify system performance in terms of sensing, communications, and lifetime as determined by energy consumption. Our approach is to begin with an established and highly capable modeling environment for communications networks, and to extend this environment to incorporate the sensing system elements, including signal processing and associated power consumption aspects. We selected the QualNet discrete-event simulation environment as the foundation for our tool development, described further in this section.

Model Design Using QualNet

There are a number of excellent, highly capable simulation environments for communications networks. QualNet has particularly advanced capabilities for modeling wireless networks. Considerable care is taken to precisely model the reception of a common signal by multiple receivers, as well as the reception of overlapping signals generated from multiple transmitters. These existing high fidelity environmental modeling constructs are useful for developing the sensor system models. Multiple communications channel modeling is incorporated, which is important for developing multi-modal sensor extensions. To model distributed sensors, an object-oriented approach is used in which sensor object interactions are “connected” by message passing.

In [14], Fishwick describes several models that can be used to model a complex system. A conceptual model may be used to give an overview of the hierarchy of abstractions and abstraction levels of the system. Each level of abstraction may be implemented using several different models. A declarative model is used for describing state transitions and events; this type of model is a finite state automata. Transitions in the declarative model can be defined according to probabilistic functions. A functional model is often used to describe a “black box” where certain mathematical computations are carried out; SensorML [15] and MatLab are often used to develop functional models. Constraint models are used to describe systems with limited resources such as power, bandwidth or systems with invariance. Spatial models are useful when there is a need to associate different behavioral rules to different parts of the covered area.

QualNet supports a hierarchical model design where hybrid models can be developed at different abstraction levels. For declarative models, it is easy to create state-transition graphs using QualNet Designer to describe system behavior. To build a functional model, one can create a state and specify the associated function in the C language. A constraint model can be built by stating the specific constraint as “guarded expressions” in the state-transition graphs. Depending on the specific spatial-dependent behavior, we can generate different spatial models for different regions.

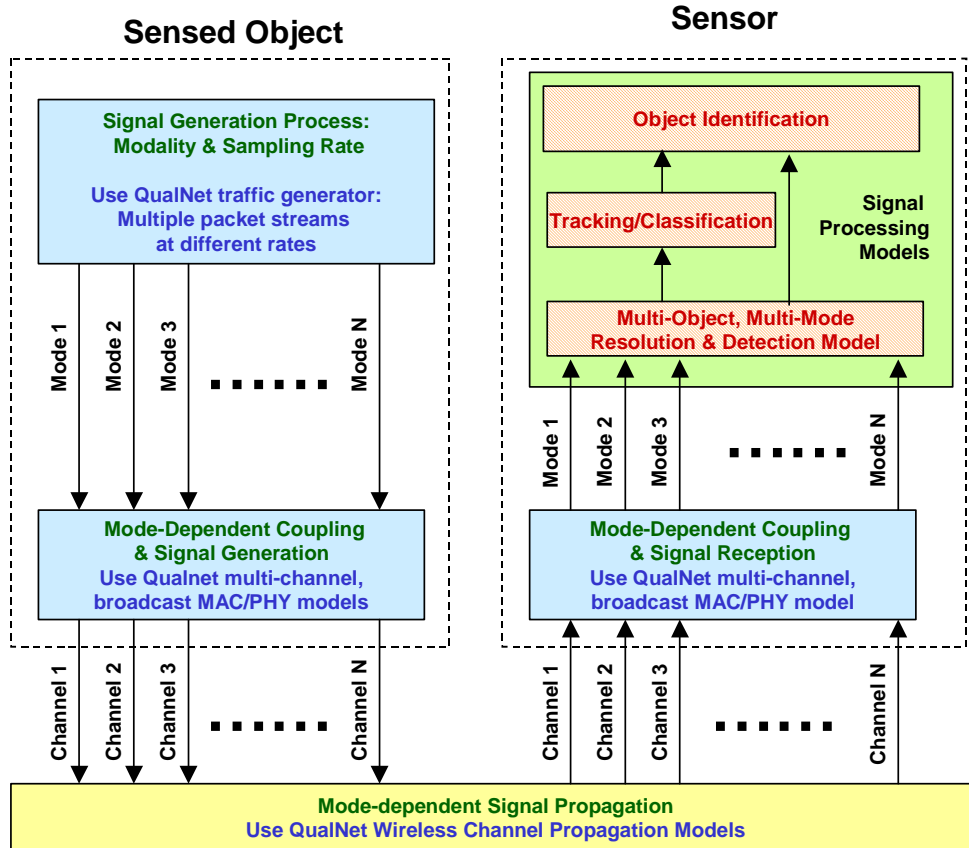


Figure 4 - Sensor System Modeling in QualNet

The discrete-event nature of QualNet provides a highly efficient means for simulating event-driven system behaviors. Event-oriented operations are typical at higher levels of system execution, such as sensor cueing or sensor fusion processes, or many communications networking aspects. However, low-level physical phenomena, such as vehicle movement or signal generation, are often continuous processes. Integrating these models is accomplished by creating time-stepped events at sufficiently short intervals to mask their quantization. The time step intervals may be tailored for each modeled phenomenon (described further in the next subsection) to maintain execution efficiency.

QualNet has built-in statistics gathering tools that facilitate system execution analyses. Generalizations needed to derive sensor system metrics can leverage these existing capabilities.

Model Implementations in QualNet

Figure 4 shows how the various components of a sensor system are modeled using QualNet. The “sensed object” and “sensor” are nodes/entities defined in the QualNet simulation environment. The “sensing” phenomenon – i.e., the signal emissions from an object and the reception of the same signal with some distortion by a sensor – is modeled as communications between nodes. Although sensor signals are in reality broadcasted continuously, we model this as a continuing periodic sequence of emissions at a certain “sampling rate” for each source object and modality, using QualNet’s traffic generator. While this method is computationally demanding, the QualNet tool is known for its efficiency and speed. This capability is very important to simplify modeling of large, complex scenarios and allow rapid executions in quantities sufficient for statistical performance characterization. Exceptionally large-scale simulation models may be executed using the parallel processing capability of the PARSEC engine within QualNet, although we have not yet required use of this advanced capability at this stage of our work.

The “sampling rate” at which periodic messages are broadcasted determines the time/spatial resolution of our simulation result and the speed of execution. The reaction time elapsed from the first instance of signal presence till the appropriate sensor output will vary depending on the nature and speed of the target, the modality of the received signal, the required length of data sample, and data processor/algorithm execution time. As long as this reaction time is comparable with sampling interval of the traffic generator, the discrete-event simulation will retain the same level of time resolution as a continuous time system. To maintain the spatial resolution in our simulation, higher sample rates are required for highly mobile objects.

QualNet inherently provides detailed radio (RF wireless) physical communications channel models. To model sensor signal generation from generally mobile targets, and

propagation of sensor signals through different media, we modify the RF physical channel models to represent various sensor phenomena. Propagation speeds and attenuation with distance are appropriately parameterized. Reception of the same target signal by multiple sensor nodes is modeled utilizing QualNet’s broadcasting features at the physical and MAC layers. Each receiver (sensor) is designed to operate correctly for directionality limitations relative to the target emitter.

Multiple targets generate sensor signals that are received simultaneously at a given sensor. These overlapping sensor signals may carry substantially useful information, unlike “collisions” or even “capture” in the radio communications case. To accurately model this, we bypass the collision detection and capture features in QualNet’s physical layer model. Information such as received signal strengths of the time-overlapping signals is passed to the sensor signal processing module that characterizes the capability of the particular sensor system to resolve and detect multiple objects simultaneously.

The Qualnet tool provides multiple communications “channels” at the physical and MAC layers, nominally for modeling different radio subnets coexisting in the same spatial area. This is a critically important capability for multi-modal sensor signal reception. A channel is associated with each sensor modality, with associated signal propagation laws defined parametrically. Every vehicle broadcasts periodic streams on every sensor “channel.” This technique enables us to capture the essential fusion behavior of spatially distributed sensors.

Last but not least, QualNet provides the capability for modeling the interactive data communications between sensors during self-organization, distributed routing and messaging, and cooperative data fusion. Combined with the sensor system models, we have an integrated sensor/communications platform for performance evaluation.

5. EXAMPLE EVALUATIONS

In this section, we illustrate the use of the QualNet tool through two types of sensor network performance cases. In the first case, we evaluate a sensor network’s ability to track a moving target using a field of simple omni-directional sensors of a single modality. The second case illustrates the simulation tool’s ability to characterize multi-modal detection of different target types.

Target Tracking Experiment

In this example, we assume that sensor nodes of a single modality are randomly (uniformly) deployed over a 1000 x 1000 meter region. We assume the sensor nodes are omni-directional “trip-wire” nodes, each with a detection range of approximately 300 meters. A single target moves through

the coverage region, with a manually constructed trajectory. Each sensor node reports the time that it first detects the target, and an ordered list (in increasing time) is formed: $\{t_1, t_2, \dots, t_n\}$. This ordering is used to index the sensor nodes. The position of sensor node i is denoted p_i , and the positions of the sensors are listed in that order $\{p_1, p_2, \dots, p_n\}$. A simple “track estimate” of the target is the continuous time function $P_{est}(t)$ that can be constructed as:

$$P_{est}(t) = \begin{cases} p_i & \text{if } t = t_i \\ p_i + \frac{p_{i+1} - p_i}{t_{i+1} - t_i} (t - t_i) & \text{if } t_i < t < t_{i+1} \end{cases} \quad (1)$$

Between instances of first detection, the location of the target is simply linearly interpolated from the two neighboring end points.

Figure 5 shows the setup in QualNet. The target has a predefined track starting from the upper-right corner of the simulation region; the sensors positions are uniformly distributed. We tested two cases, using 36 and 49 sensor nodes. Intuition tells us that using more sensors should give us better tracking accuracy.

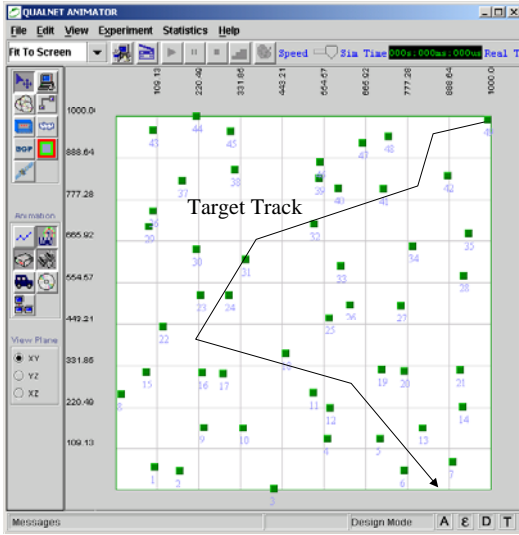


Figure 5 - QualNet Tracking Experiment

Figure 6 compares the actual track with the estimated tracks derived from the initial target detection times and the sensor positions. The red (solid) line shows the actual track, and the blue (dotted) and the green (dashed) lines represent the estimated tracks produced by using 49 and 36 uniformly distributed sensor nodes respectively. For illustration, we marked the actual and estimated target position at $t = 120$ sec. Visual inspection shows that the 36-node case (green dashed line) actually produced a smoother track in comparison to the 49-node case. The “zig-zags” in the latter case result from the target being initially detected by different nodes over relatively short time spans.

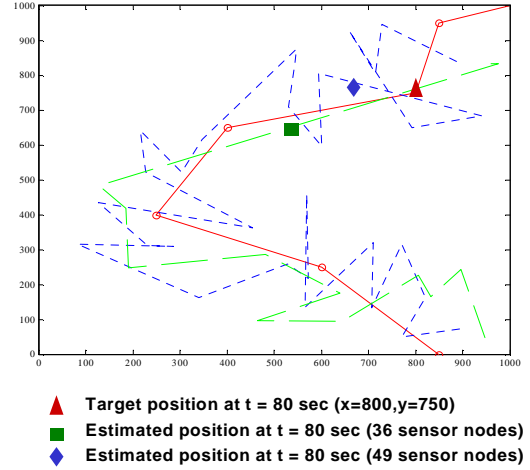


Figure 6 - Tracking Results

To compare the tracking accuracies quantitatively, we compute the average tracking error as the average distance between the actual track and the estimated track. Let $P_{target}(t)$ be a two-dimensional vector representing the actual coordinate of the target at time t . $P_{est}(t)$ is the estimated target location at time t , and T is the duration of the tracking operation. Then the tracking error is given by:

$$\epsilon_{track} = \frac{1}{T} \int_0^T \|P_{target}(t) - P_{est}(t)\|_2 \cdot dt \quad (2)$$

Applying this metric, we find that $\epsilon_{track} = 161.14$ meters when using 49 nodes, and $\epsilon_{track} = 188.02$ meters using 36 nodes. We can clearly see that our intuition regarding the benefit of using more nodes is correct, although it was not visually obvious.

It is clear that this simple tracking estimator could be substantially improved. In particular, use of the complete detection interval for each sensor contains additional useful information than just the initial detection time. Further improvement can be made based on trajectory constraints and the relative sensor node positions. When the target is detected simultaneously by multiple nodes, greater accuracy could be derived from coherent combining of data in order to triangulate the target’s location. Different tracking algorithms, with dissimilar complexity and communications needs, will be modeled in the simulation tool so that the sensitivity of sensor node spatial density (and other system choices) on tracking performance can be derived.

Multi-modal Sensors, Multiple Target Types Experiment

The second illustration of the simulation tool also presumes an “unconstrained corridor” scenario, in which each target can move generally within a two-dimensional region. The nominal sensor network architecture is hierarchical, consisting of trip-wire nodes at the lowest level, pointer nodes at the middle level, and tracker/ID nodes at the highest level. Each pointer node (nominally an integrated

beamforming array) is capable of determining target bearing at long range, but consumes energy at a high rate. To conserve energy, the pointer nodes will “sleep” until they are awakened by trip-wire nodes. The trip-wire nodes provide the basic “detection” functionality. When a trip-wire sensor detects a target, it will cue the pointer nodes by sending an alert message. Upon receiving an alert message, one or more pointer nodes will shift into active mode and begin scanning the vicinity of the reporting trip-wire node for the target and try to determine the target’s bearing in relation to its own position. The bearing information from several pointer nodes can then be communicated to a tracker/ID node for fusion so that the target position can be computed; classification/identification of the target type is also determined. By continuously monitoring the target and fusing the bearing information, a track is created and can be relayed to users to provide situational awareness.

Note that this is a considerably more sophisticated sensor system architecture than that of the previous example. In this set of experiments, we focus solely on the lowest tier of this sensor network hierarchy. The goal is to determine the detection performance for the trip-wire nodes. Also, within any complete operational scenario, there are three key components: (1) *sensing*, (2) *communication*, and (3) *energy*. However, the following focuses on the *sensing* component alone. The key metrics are probability of target detected, latency, and target exposure. This experiment demonstrates the use of the multi-channel capability of our simulation platform to model multi-modal sensing with respect to different target types.

We define two types of target {A, B} and two types of sensors that are either of modality X or Y. A total of 25 sensor nodes, with variable mixture of mode X and mode Y, are laid down within a 1000m by 1000m region. The sensor nodes are placed randomly across the region according to a uniformly distributed distribution. At any time, there is only one target moving across the region. Random tracks are generated for each target according to a process that produces tracks of generally similar lengths (i.e., tracks cannot cut across a small fraction of the coverage area). This latter constraint ensures that the detection metric is fair.

We assume that a type A target is easier to detect than a type B target by a sensor of modality Y; while the situation is reversed for sensors of modality X. This is shown in Figure 3, where $r_{X,A}$, $r_{X,B}$, $r_{Y,A}$, and $r_{Y,B}$ denote the average detection ranges for sensors of modality X or Y with respect to targets of type A or B respectively.

Obviously, if we were only concerned with one type of target, then we would use exclusively the sensor modality that is optimal for that type of target. However, when there are at least two types of targets of interest, performance can be optimized by analyzing the trade-off among different mixtures of sensor modalities.

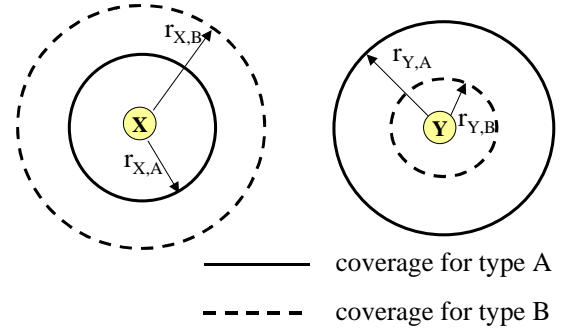


Fig. 7 - Multi-modal Sensing for Different Target Types

To be more specific, we assume modality X corresponds to a seismic sensor and modality Y corresponds to an electric field sensor. Suppose that the type A target is a lightweight wheeled vehicle whose average detection ranges for seismic and electric field sensors are 15m and 50m respectively. The type B target is a heavy wheeled vehicle having a strong seismic signature, but has electric field shielding, so that the corresponding detection ranges are 50m for seismic and 8m for electric field signatures. By varying the mixture of modalities in the deployed sensors, we can trade off the coverage provided for the different types of targets. Given these average detection ranges, if only modality Y sensors are used, the maximum coverage for target type A is 19.6% but only 0.5% for target type B. Using an even mixture of mode X and mode Y sensors, however, will produce approximately 10.45 % coverage for target type A and 11.05% for target type B.

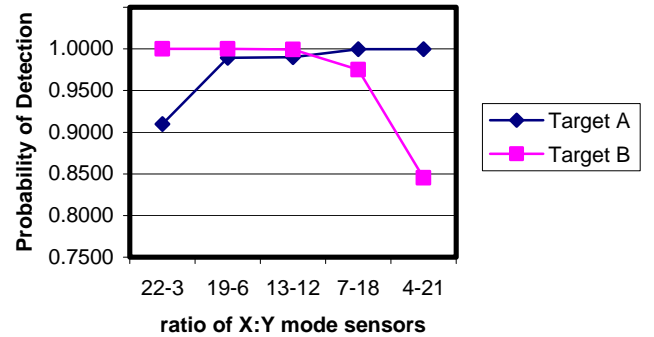


Figure 8 - Probability of Detection vs. modality mix

For different mixtures of sensor modalities, 10,000 tracks are generated in our simulation to generate performance statistics. Figure 8 shows the probability of detection for both type A and type B targets under different mixtures of sensor modalities, illustrating the trade-off in favoring one modality over the other. Overall detection probability is 98% or better when there is a more balanced mixture. However, an asymmetric cost in detection failure of target type could influence the choice of sensor deployment mix.

Figure 9 shows the average first detection time for a target versus the sensor modality mix ratio. We can translate the

latency into actual physical distances based on the target's constant speed of 40km/hr. For example, the maximum average latency for type A is about 34 seconds when the X:Y ratio is 22:3; this means the target can traverse an average of 377 meters inside the region of interest without being detected. This gives the user a rough idea of the "buffer zone" one needs between the edges of the sensor field and the assets or personnel one wishes to protect against enemy penetration. (Recall the sensor field is sparse with average coverage around 10 to 11%.) If we treat both types of target with equal importance, then a ratio of 19:6 is the optimal in minimizing the combined detection latency of the system.

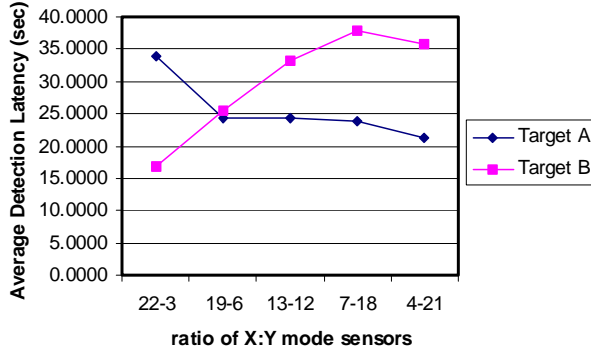


Figure 9 - Average Detection Latency

Figure 10 shows the normalized 0, 1, and 2-exposure periods. The normalized 0-exposed period is the "blind" period during which target traverses within the sensor field "unseen." This metric can change from nearly 95% down to 60% by changing the mixture of sensor modality. The blind period is large in our experiment because we are considering a sparsely populated sensor field. Large blind periods are very challenging for tracking algorithms because sporadic observations must be pieced together into a coherent track with high level of confidence. Furthermore, the 2-exposure period is quite small (less than 0.5%), again due to the sparse sensor node laydown, and therefore opportunities for coherent data fusion (e.g., beamforming) are rare. However, this configuration is consistent as the lowest tier in the hierarchical sensor architecture, and provides good target detection performance toward cueing the next tier of pointer sensors. An alternative sensor node architecture that is "flat" and attempts to utilize beamforming among nodes that simultaneously view the target would require a much greater spatial density of nodes. As we complete our development of directional sensor models (for pointer nodes), comparative analyses will be determined.

6. CONCLUSIONS

In this paper, we presented a novel approach for determining the performance of sensor networks. An integrated simulation tool, based on the QualNet discrete-event simulation environment, provides the means to evaluate sensing, communications, and energy consumption metrics.

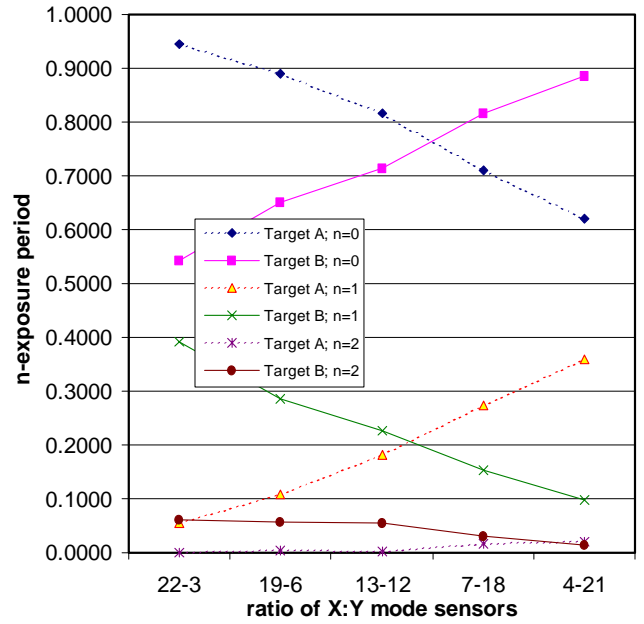


Figure 10 - n-exposure performance vs. modality mix ratio

The sensing aspects are represented by extending communications models. Sensing of multiple target objects by multiple sensor nodes is simulated using broadcast and multiple access constructs and modifications, and multi-modal sensing is modeled using multiple channel techniques. Use of the system evaluation tool has been illustrated by examples of a field of sensor nodes deployed over a region and its ability to sense a moving target. These examples show the performance impacts of different sensor network configurations, including the target track quality as a function of the spatial density of sensor nodes, and the probability of detection for different target types as a function of multi-modal sensor mix. This tool is expected to play a critical role in evaluating emerging sensor network technologies, ranging from component microsensor and wireless communications advancements to decentralized fusion architecture, sensor system management and integrated communications networking innovations.

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